Doing Science Faithfully

Or: can a niche application to evaluate charges of cheating at chess inform statistical practice in medicine, both for focus on human reality and defending against drives to unreality?

Kenneth W. Regan[1]
University at Buffalo (SUNY)

17 April, 2026

[1]With grateful acknowledgment to co-authors Guy L. Haworth and Tamal Biswas, students in my graduate seminars, and UB's Center for Computational Research (CCR)

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- But also: pursuit of *transgression* needs to allow for *redemption*.

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To have a Predictive Analytic Model **IMPHO** means that it:

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- **Multiple-choice tests**: m_i are possible answers to a test question, u_i = gain/loss for right/wrong answer.

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(source: itunes.apple.com)

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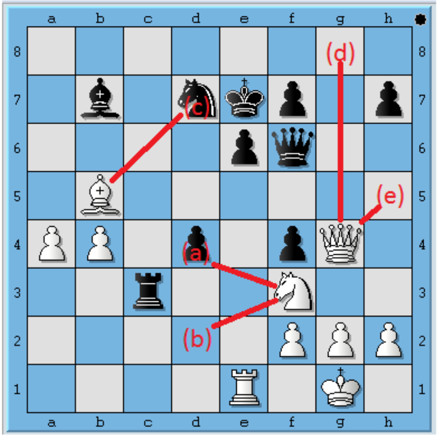

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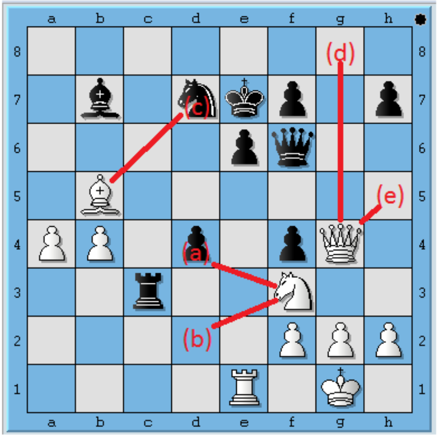

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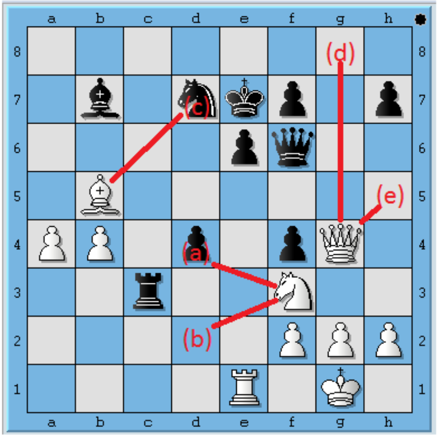

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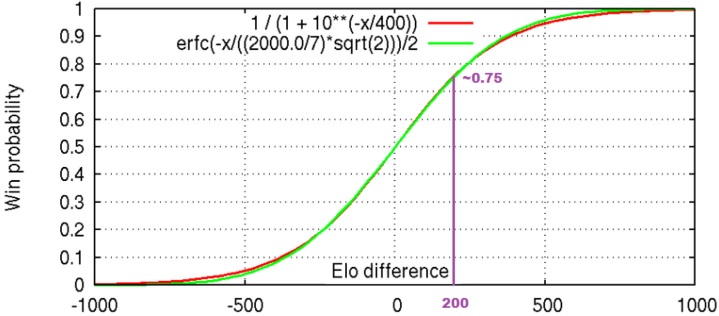
- Expectation given by rating *difference* via this logistic curve:



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- An **Intrinsic Performance Rating** (**IPR**) for the set of games.

Fit s, c, h by making T1,EV,ASD be **unbiased estimators** on the training sets, which are stratified by Elo ratings.

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- Analogy: if you know your rain-forecasting accuracy, but 100-year floods happen every 5 years, you may conclude that Mother Nature is cheating with a systematic heat source.
- This test is so far no stronger or weaker than my original based on MM and CPL metrics.

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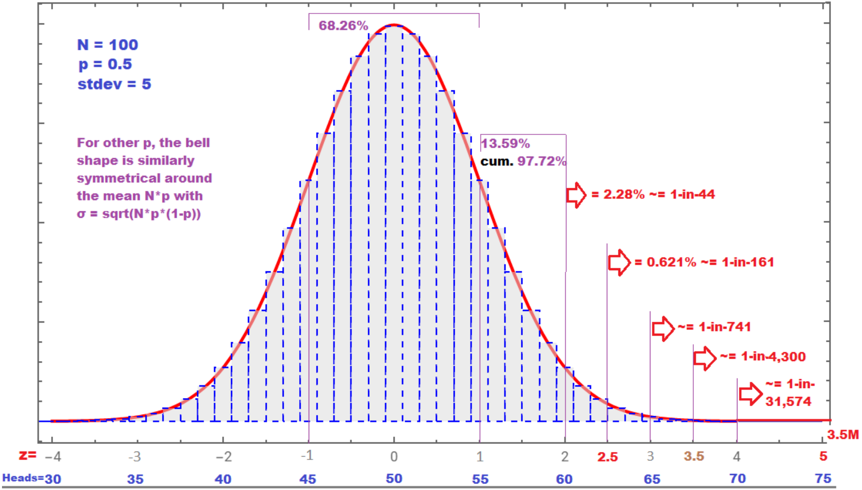
- 4σ = 32,000–1;
- 3σ = 740–1;
- 2σ = 43–1 (civil minimum standard, polling "margin of error").

Bell Curve and Tails



Blue = binomial 100 scale of the **screening stage**. WSTC examples.

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- **Look-Elsewhere Effect**: How many were playing chess that day? weekend? week? month? year?
- **"Shiny Marbles Get Noticed"**—and this influences the **conditional probability** associated to a possibly suspicious observation.

Over large datasets from (presumably) non-cheating players, the **Central Limit Theorem** "kicks in" well: the z-scores conform to the bell curve. Example Spreadsheets.

Some Example Cases (old ones on-purpose...)

Cheating and ...

- Sebastien Feller, 2010 Olympiad, rated **2649**.
  - 4 confessed all-cheating games: **z=2.96** with IPR **3240**.
  - 5 other games: IPR **2547**.
  - Fact of on-site evidence made these results significant.
- Borislav Ivanov, 2012 Zadar Open, rating 2227→2342.
  - Z-scores as high as **5.10**.
  - IPR near **3100**.
  - FIDE now allows verdict "assumed cheating" by stats alone.

[Results from model built using old Rybka 3 engine]

Non-Cheating

- Kramnik-Topalov World Championship Match, 2006
  - Topalov's manager accused Kramnik's moves in games 1—6 with the engine Fritz 9.
  - I reproduced the claimed 90% concordance only in the second half of Game 2.
  - Still matches 26-of-32 (**81%**) to both Stockfish 11 & 16.
  - But my model projects **82%** concordance there---most of those moves were "forced" hence relatively easy to find.

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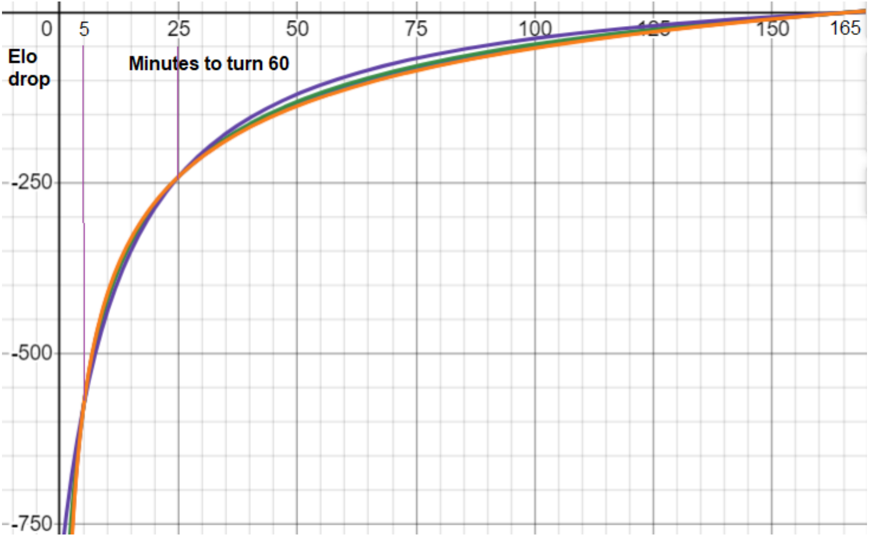
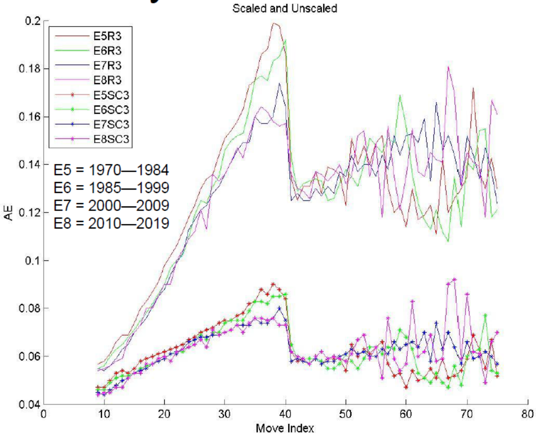
Let's consider elements of **difficulty** and **time usage**.

Time-Quality Curves (whole graph)



Time Usage, Procrastination, and Centipawn Loss

Error By Move Number in Games



Effect of time pressure approaching Move 40 is clear.

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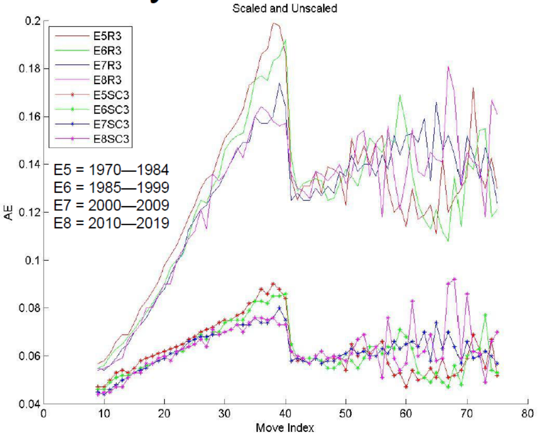

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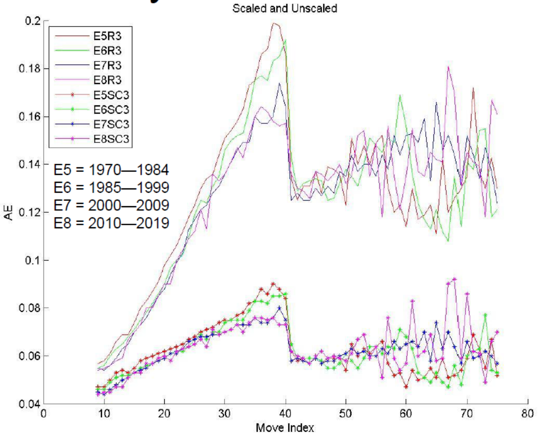

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(How) Can we teach players to use time with more foresight?

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- Positions with 5–10 minutes consumed (729 pos.): **650 +- 235**.
- Using 10–15 minutes (168 positions): **465 +- 565**.
- Using $\geq$ 15 minutes (104 positions): **700 +- 505**.

Thinking is Bad For 8-Year-Olds Too!

After 3 rounds of the **2024 World Cadets Championships** in separate Open and Girls' sections of ages **U08**, **U10**, and **U12**.

- The two **U08** sections combined have average rating **1596**.
- I measure IPR as **1525 +- 45**. (10,913 positions total)
- Positions on which they spent at most **30 seconds** on the move: **2170 +- 125** (2,996 pos.)
- At most **10** seconds: **2860 +- 245** (632 positions)
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- **What's going on here?**

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- **Temptation**: set lower rating R on longer-think moves.

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- Q & A, Discussion, and Thanks.

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7. Find people to talk to...and compare results.

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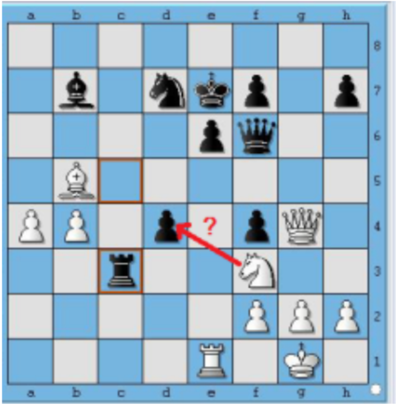
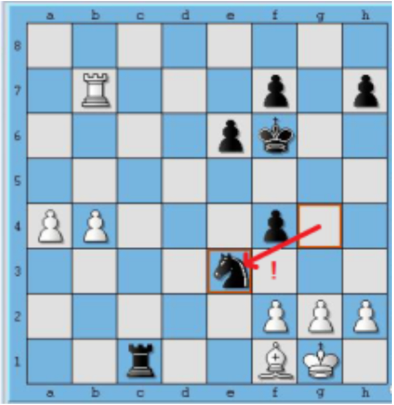
  - We will try to glean comparable insight from numerical analytics.

Move Utilities Example (Kramnik-Anand, 2008)





Depths... Values by Stockfish 6

Move	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Nd2	103	093	087	093	027	028	000	000	056	-007	039	028	037	020	014	017	000	006	000
Bxd7	048	034	-033	-033	-013	-042	-039	-050	-025	-010	001	000	-009	-027	-018	000	000	000	000
Qg8	114	114	-037	-037	-014	-014	-022	-068	-008	-056	-042	-004	-032	000	-014	-025	-045	-045	-050
...			...			...			...			...			...			...	
Nxd4	-056	-056	-113	-071	-071	-145	-020	-006	077	052	066	040	050	051	-181	-181	-181	-213	-213

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- Other than these, **my model knows nothing about chess.**

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The generic **log-linear** model puts

$$\log\left(\frac{1}{p_i}\right) = \alpha + \beta u_i, \quad \text{or equivalently,} \quad \log\left(\frac{1}{p_i}\right) - \log\left(\frac{1}{p_1}\right) = \beta\delta_i$$

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- So p_i are represented as **powers** of the best-move probability p_1.
- In place of $\beta\delta_i$, I really have $\left(\frac{\delta_i - h\rho_i}{s}\right)^c$, with h tightly clamped.

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